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AI-BASED RECRUITMENT AND APPLICANT TRUST: THE ROLE OF PERCEIVED FAIRNESS AND AI LITERACY

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Abstract

The use of artificial intelligence in recruitment has grown quickly, yet many job applicants remain uncertain *whether AI-based hiring systems will treat them fairly. Drawing on organizational justice theory, this study examined the effect of AI-based recruitment on applicant trust, the mediating role of perceived fairness in this relationship and the moderating role of AI literacy. Data were collected through an online survey from 318 job applicants in Lahore, Karachi and Islamabad, Pakistan, who had applied for jobs through processes involving AI-enabled tools during the previous twelve months. The data were analyzed with partial least squares structural equation modelling in SmartPLS 4. The results showed that AI-based recruitment had a positive effect on both applicant trust and perceived fairness, and that perceived fairness had a positive effect on applicant trust. Perceived fairness partially mediated the relationship between AI-based recruitment and applicant trust, while AI literacy strengthened the positive effect of AI-based recruitment on applicant trust. These findings extend organizational justice theory to AI-based hiring by showing that applicants' trust in such systems depends largely on whether they view the process as fair, and that applicants with a better understanding of AI respond more positively to it.*

INTRODUCTION

Recruitment has changed considerably over the past decade as organizations have moved from manual screening towards digital and automated hiring tools. Artificial intelligence (AI) is now used at several stages of the hiring process, including writing job advertisements, searching for candidates, screening résumés, running chatbot conversations with applicants and assessing recorded video interviews (Black & van Esch, 2020; Upadhyay & Khandelwal, 2018). AI-based recruitment refers to the use of these systems to collect, analyzes and evaluate applicant information in order to support or make hiring

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decisions. Organizations adopt such tools mainly because they promise faster handling of large applicant pools, lower hiring costs and more consistent decisions than human recruiters can usually offer (Pan et al., 2022).

In recent years, AI has rapidly become a part of the hiring process. In 2025, 43% of organizations utilized AI for human resource tasks, up from 26% in 2024, with recruitment being one of the top areas where AI is applied. The applicants' perspective is quite different, however. According to Gartner, a survey of 2,918 job candidates revealed that only 26% trust AI to fairly assess them, while a Pew Research Center survey of over 11,000 U.S. adults found that 71% are against using AI in the final hiring process. Technology professionals were not much more trusting of AI-driven hiring systems, with 68% reporting they didn't trust them (Dice, 2025). Additionally, regulators have reacted to these concerns, and the European Union's Artificial Intelligence Act now considers AI systems used for recruitment and selection as high-risk, imposing further obligations on the organizations using them (European Union, 2024). These statistics indicate that the employer is rapidly adopting AI hiring and that many candidates are not certain about how fair AI hiring is.

This gap between organizational adoption and applicant acceptance is important because applicant trust influences the applicant's reaction to the recruitment process. Trust can be defined as an applicant's readiness to depend on a system of hiring and to endorse its results, although an applicant may not be able to see or control the decision-making process (Mayer et al., 1995). If applicants don't believe in a selection process, they are more likely to opt-out, to have a negative opinion of the employer and to share that opinion with other job seekers (Gilliland, 1993; Langer et al., 2019). Trust is more difficult to establish in the case of AI, as applicants typically don't have visibility into how the AI arrives at its decisions. The public has been told about numerous cases, such as the recruiting tool Amazon abandoned after it was found to be negatively affecting female applicants (Dastin, 2018), which have led to doubts around algorithmic hiring (Glikson & Woolley, 2020; Köchling & Wehner, 2020).

While there has been growing research on AI in recruitment, there are still a number of questions that have yet to be answered. First, most research so far has focused on how organizations use AI in recruitment, such as decisions to adopt, potential efficiency gains, and ethical concerns (Hunkenschroer & Luetge, 2022; Pan et al., 2022), but there is less research that has explored applicants' reactions to these systems. Second, studies which do include applicants have mixed results. Some demonstrate that algorithmic decisions are perceived as less fair and less trustworthy than human decisions (Lee, 2018; Mirowska & Mesnet, 2022; Newman et al., 2020), and others demonstrate that in some cases people prefer algorithmic judgements over human judgements (Logg et al., 2019). The mixed findings suggest that the impact of AI in recruitment on applicant trust could be mediated by applicants' perceptions of fairness; however, the perceived fairness has rarely been studied as a mediator between the two. Third, there is little knowledge of the situations where this relationship is enhanced and diminished. Understanding the differences between those who accept AI in hiring and those who do not may be related to AI literacy, which is defined as the capacity of an individual to comprehend, assess and apply AI technologies (Long & Magerko, 2020; Ng et al., 2021), but has not been extensively explored in the recruitment context. Lastly, the empirical evidence is mainly from North America and Europe, with less known about applicants in other areas where AI hiring tools are now being implemented.

To explain these relationships, this study is based on the organizational justice theory and specifically on Gilliland's (1993) model of applicant reactions. The theory suggests that the applicants' perception of the consistency, bias, job relatedness, and explainability of the procedures in the selection system influences their attitudes

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toward the selection organization (Colquitt, 2001; Gilliland, 1993). With this in mind, AI in recruitment should impact applicant trust by how fair they perceive the recruitment process to be. Applicants who are more knowledgeable about AI are also likely to react differently to AI-based recruitment, as they will be less uncertain and will have more or less trust in the systems.

Based on these issues, the present study examines the effect of AI-based recruitment on applicant trust, the mediating role of perceived fairness in this relationship and the moderating role of AI literacy. The study is significant to employers and employees. Job seekers' perception of fairness and trust in AI-driven recruitment can either enhance or detract from the value of AI for employers. The results are relevant to the ongoing work of job seekers and policymakers on efforts to increase transparency and accountability in the use of AI in employment decisions.

This study has three key contributions. It first contributes to the literature on applicant reactions to recruitment by exploring the applicant's perspective on AI-based recruitment, instead of the employers. Second, it expands the organizational justice theory to the context of AI-based hiring, and it examines the perceived fairness as the underlying process of the impact of AI-based recruitment on the trust of applicants. Third, it recognizes AI literacy as a boundary condition, meaning that it helps to explain the differences in applicants' trust in AI-based hiring. The results have real-world implications that can inform human resource managers to create transparent and equitable recruitment processes using AI, and can assist in building AI literacy among job seekers.

Theoretical Foundation

The research is based on the theory of organizational justice and in particular on Gilliland's (1993) model of applicant reactions to selection systems. Organizational justice theory explains how people judge the fairness of decisions and procedures in the workplace, and how these judgements shape their attitudes and behaviour towards the organization (Colquitt, 2001; Colquitt et al., 2013). Gilliland (1993) applied this theory to recruitment and argued that applicants judge a selection system by a set of procedural rules, such as consistency of treatment, job relatedness, the chance to show their abilities, two-way communication and the explanation of decisions. If these rules are followed, applicants perceive the process as fair and they have more positive attitudes toward the hiring organization.

The theory comes in handy when it comes to AI in recruitment, as the algorithms alter the way these procedural rules are delivered. The same criteria can be applied to all applicants, and AI systems can minimize the impact of personal bias, thereby helping to uphold the rule of consistency (Langer & Landers, 2021). Meanwhile, AI systems can reduce the importance of two-way communication and explanation, and they may lack the ability to explain the rationale behind their decisions (Babaee & Shank, 2025; Malin et al., 2025). Applicants thus make fairness judgements on the basis of how well the AI-based recruitment process fits with these rules, which in turn influence their trust in the process.

This explanation can be complemented by the fairness heuristic theory, which demonstrates the close relationship between fairness and trust. Lind (2001) claimed that it is not always possible to make a direct assessment of whether an authority is trustworthy or not, and therefore people rely on their perception of fairness as a mental shortcut to determine whether to trust an authority. In AI recruitment, the applicant typically does not have insight into the functioning of the algorithm, and this lack of insight is particularly relevant to the formation of perceptions of fairness as a foundation for trust (Starke et al., 2022). Organizational justice theory also indicates that procedures will be interpreted differently by individuals. Knowledge about how AI systems function enables applicants to evaluate the consistency, accuracy, and lack of bias in an AI-driven process (Long & Magerko, 2020; Pinski &

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Benlian, 2024). For that reason, AI literacy is predicted to impact applicant responses to AI-powered recruiting.

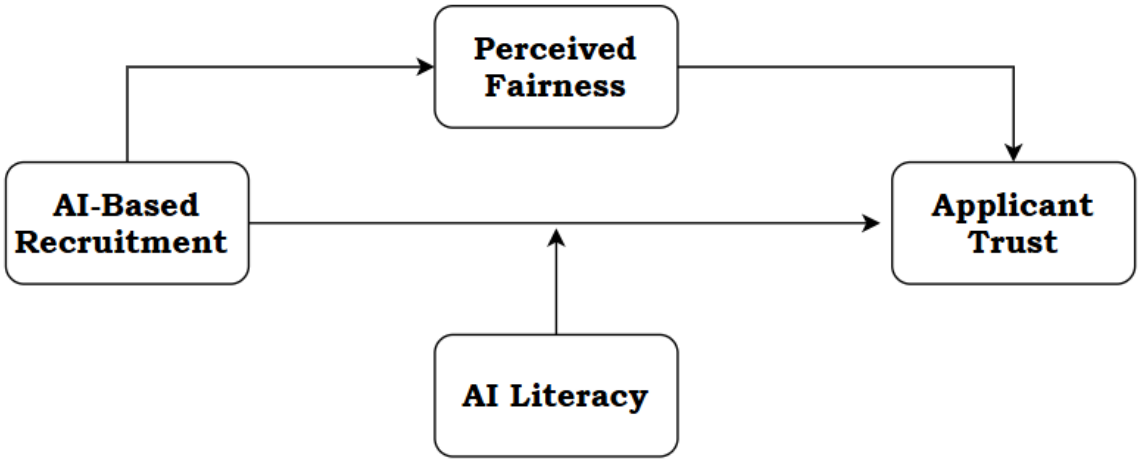


Figure 1: Research Model (Self Developed by the researcher)

Hypotheses Development

Applicant trust is the applicant's belief in the hiring process and the willingness to accept the results of the process, despite the lack of complete observation and control on the part of the applicant (Mayer et al., 1995). Trust is important in recruitment because applicants are providing personal information to the employer and relying on the employer to assess this information in an honest and competent manner. This trust can be impacted by AI in recruitment in a few ways. By eliminating the impact of a recruiter's mood, fatigue, or personal preferences, AI systems can evaluate a large number of candidates based on the same criteria, reducing the risk of bias or subjective judgment. (Black & van Esch, 2020; Langer & Landers, 2021). Algorithmic judgements have been proven to be more influential than human judgements in the case of objective information (Logg et al., 2019). Similarly, according to survey data, nearly half of U.S. adults say that they think that AI would treat applicants better than human recruiters, when it comes to equality (Pew Research Center, 2023). These can create an impression of transparency and a merit-based application process that is a foundation of trust for applicants.

The evidence of this association is not entirely clear, however. According to some studies, applicants are not as confident in hiring by AI compared to hiring by humans, primarily due to the decreased level of personal interaction and fewer opportunities to explain themselves (Babaee & Shank, 2025; Mirowska & Mesnet, 2022). Other research demonstrates that these negative responses may be mitigated by an organization's explanation of the use of AI, and when the system is perceived as accurate and consistent (Gonzalez et al., 2022; Malin et al., 2025). This indicates that it's not just about the AI itself, but the applicant's journey through the AI-driven process. Applicants are more inclined to trust and accept the results of AI-based recruitment when they perceive it as efficient, consistent and job-related information. Organizational justice theory suggests that a process that treats all equally, and that does not allow for too much personal bias to be involved, is consistent with key procedural rules, and

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applicants are more likely to trust such a process (Gilliland, 1993). Therefore, the following hypothesis is proposed:

H1: AI-based recruitment has a positive effect on applicant trust.

Perceived fairness is the extent to which applicants feel that the process of assessing them and the results of the process are fair and appropriate (Gilliland, 1993). Perceptions of fairness are some of the most frequently investigated responses in selection research because it can affect applicants' attitudes toward the employer, their acceptance of job offers and their recommendation of the organization to others (Colquitt et al., 2013). The fairness perceptions in AI-based recruitment rely on the degree of compliance of the AI system to the procedural rules that applicants anticipate. There are a number of features of AI-based recruitment that support these rules. AI systems use the same criteria and the same method of scoring, which is in line with the rule of consistent treatment (Langer & Landers, 2021). AI tools can also be configured to only pay attention to information that is relevant to the job, e.g., skills, qualifications and experience, and not to personal characteristics unrelated to the job (Hunkenschroer & Luetge, 2022).

Recent research backs this up; the findings will vary based on the application of the AI system. Malin et al. (2025) discovered that if the AI decisions were communicated to the applicants, their perception of fairness was comparable to, or in some instances even greater than, their perception of human decisions. Gonzalez et al. (2022) also found that when AI was used to assist human recruiters in hiring processes, applicants were more positive. Other studies find that applicants may perceive algorithm-based processes as less fair when they believe that the system fails to consider attributes that are hard to quantify (Lavanchy et al., 2023; Newman et al., 2020). The results suggest that the impact of the use of AI in recruitment on fairness is contingent upon whether the applicant perceives the process as consistent, accurate, and relevant to the job. Structured and transparent use of AI is likely to be perceived by applicants as treating them fairly and assessing them fairly based on merit. Starke et al. (2022) also reported that a sense of consistency and decrease in bias are among the key factors that make people consider algorithmic decisions to be fair. Based on these arguments, the following hypothesis is proposed:

H2: AI-based recruitment has a positive effect on perceived fairness.

Fairness and trust have been well documented in the organizational justice literature. Meta-analytic evidence indicates that those who perceive an organization treats them fairly, report increased trust in the organization and in its decision makers (Colquitt et al., 2013). Fairness heuristic theory is a possible explanation for this connection, as people often do not have the information to assess whether an authority can be trusted and therefore draw inferences based on fairness perceptions to make a decision about whether or not to rely on the authority (Lind, 2001). Fair procedures lead to the belief that the authority will not take advantage of them, and they are more willing to accept the authority's decisions.

This is particularly true when it comes to AI recruitment. It is common for applicants to not have direct access to the data, rules or models used by an AI system to assess them, making it hard to directly assess the system's reliability (Glikson & Woolley, 2020). In this context, applicants will probably be guided by their perception of the fairness of the process in deciding whether or not to trust it. This is backed up by research on algorithmic decision making. In particular, Shin and Park (2019) indicated that perceptions of fairness, accountability and transparency boosted the trust in algorithmic systems, and Shin (2021) indicated that explanations enhanced the trust in AI predominantly by improving users' judgments of the system. In the hiring context, Babaee and Shank (2025) discovered that there was a close relationship between the perception of procedural

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justice and trust in the hiring process and both influenced the attraction to the organization. Langer et al. (2023) also found a dramatic drop in trust when participants perceived unfair bias in automated systems, suggesting that fairness is a key factor in trust with AI. Applicants are more likely to think the employer is doing the right thing and doing it well when they feel the standards are applied fairly to all and that relevant information is used and reasonable explanations are provided in an AI-based process. Therefore, the following hypothesis is proposed:

H3: Perceived fairness has a positive effect on applicant trust.

The above hypotheses imply that there is a relationship between AI-based recruitment and perceived fairness, and between perceived fairness and applicant trust. These relationships suggest that perceived fairness might serve as a mediator between the use of AI in recruitment and trust in the applicant. Organizational justice theory is relevant to this mediating role as it suggests that the characteristics of a selection procedure do not directly affect applicant attitudes, but rather through the applicants' assessment of the fairness of the procedure (Gilliland, 1993). Applicants first notice the procedure and then make fairness assessments based on the procedure rules, the fairness assessment will further influence their attitude and behavior to the organization.

In this perspective, AI in recruitment does not inherently lead to a loss or gain of trust. Rather, they will be more inclined to trust an AI-based process if they feel like it is consistent, relevant to the work, and unbiased. This explanation is confirmed by several recent studies. However, the negative impact of AI-driven hiring on applicants' organizational attraction was nullified when procedural justice and trust in the process were added as variables, demonstrating that the effect of AI-driven hiring on applicants' organizational attraction was mediated by their procedural justice and trust in the process. Similarly, Malin et al. (2025) found that applicant reactions to AI decisions were primarily influenced by the explanations, which increased fairness perceptions. Also, outside of recruitment, research indicates that the perception of fairness is a key driver for users to accept or reject algorithmic decisions (Shin, 2021; Starke et al., 2022). According to fairness heuristic theory, since applicants are unable to see the way the AI system draws its conclusions, they are guided by fairness judgements as the primary basis for determining whether or not to trust the AI system (Lind, 2001). Thus, the use of AI in recruitment is likely to lead to an improvement in the perceived fairness and consequently, the trust of applicants. This leads to the following hypothesis:

H4: Perceived fairness mediates the relationship between AI-based recruitment and applicant trust.

AI literacy is defined as an individual's capacity to comprehend AI, its operation, its capabilities and limitations, and how to critically assess its output (Long & Magerko, 2020; Ng et al., 2021). AI literacy is not uniformly distributed across individuals, and individual variability in AI literacy influences their interactions with AI systems in their daily lives and professional environments (Pinski & Benlian, 2024; Wang et al., 2023). In recruitment, the AI literacy may impact on how applicants perceive and respond to an AI-driven process. When AI hiring tools are not well designed, applicants with low AI literacy may perceive them as unfamiliar and hard to understand, resulting in uncertainty and a lack of trust in the process (Glikson & Woolley, 2020). Applicants with high AI literacy, on the other hand, are more likely to understand how AI systems gather and analyze information, enabling them to assess the process based on its actual characteristics instead of worries about AI.

The connection between AI literacy and trust has been backed by recent studies. Wang et al. (2026) determined that AI literacy directly and indirectly boosted users' trust in AI by enhancing their emotional reactions towards AI systems. Pinski

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and Benlian (2024) further stated that higher levels of AI literacy led to better use of AI and to relying on AI more confidently. This can be explained by the organizational justice theory which states that the less uncertain people are, the more they can assess whether a procedure is consistent and accurate (Lind, 2001). Thus, those who are more literate in AI are likely to perceive the consistency and work-relatedness of AI-based recruitment and this perception will likely reinforce the positive impact of AI-based recruitment on trust. Low AI literacy among applicants can lead to a lack of understanding about the recruitment process, further reducing the connection between AI-driven recruitment and trust. Based on these arguments, the following hypothesis is proposed:

H5: AI literacy moderates the relationship between AI-based recruitment and applicant trust.

Methodology

The study was conducted in Pakistan, where in recent years, the use of digital hiring tools has increased especially in the banking, telecommunication, information technology and fast-moving consumer goods industry. Many of the big companies in these industries had shifted to online applicant tracking systems, automated CV screening, online aptitude tests and recorded video interviews, and an increasing number of graduates had applied for jobs using these systems. This created a suitable context in which to analyze the reactions of applicants to AI-driven recruitment in Pakistan and also addressed the dearth of evidence regarding this in developing economies. The population was limited to job seekers in Pakistan who applied to a job in the last year via a recruitment process where at least one step was automated by AI. Respondents were selected from the three major cities of the country, Lahore, Karachi and Islamabad, as a majority of large employers who use AI-based hiring tools reside in these cities.

A complete list of applicants who had experienced AI based recruitment was not available, therefore the study used purposive sampling (Etikan et al., 2016). Two screening questions were included at the beginning of the questionnaire. The first question was whether the respondent had applied for a job in the past year, and the second question was if any part of the application process – including CV screening, online testing, chatbot communication, or video interview assessment – had been done through an automated or AI-based process. Respondents who answered no to either question were not allowed to proceed.

G*Power 3.1 (Faul et al., 2009) was used to determine the minimum sample size. Medium effect size was 0.15, significance level was 0.05, statistical power was 0.95 and the number of predictors was 4, the minimum sample was 129 respondents. A larger sample was aimed at to enable incomplete answers and to enhance the stability of the estimates.

Data collection was done by an online questionnaire using Google Forms from February to April 2026. The survey link was disseminated via university alumni networks, career development offices of six universities, professional LinkedIn groups and graduate job-seeker groups on WhatsApp and Facebook. The questionnaire was given in English language as the respondents were university graduates who had applied for professional jobs and English is the primary language of the recruitment of such jobs in Pakistan. Before the main survey, a pilot study was conducted with 35 job applicants to check the clarity of the items and the time needed to complete the questionnaire. Some wording changes were made from their feedback to three items. The final sample did not include pilot responses. 450 questionnaires were sent out and 342 were returned. A total of 318 responses met the criteria for use after discarding 24 responses that failed the screening questions, that contained missing values on more than 10% of the items and/or showed straight-lining patterns, resulting in a usable response rate of 70.7%. To check for

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non-response bias, the responses of early and late respondents were compared on all main constructs as suggested by Armstrong and Overton (1977) and no significant difference was found. Partial least squares structural equation modelling (PLS-SEM) was used to analyze the data using the SmartPLS 4 software (Ringle et al., 2022).

Respondent Profile

Of the 318 respondents, 61.3% were male and 38.7% were female. Most respondents were aged between 21 and 30 years, which accounted for 72.6% of the sample, followed by those aged 31 to 40 years at 22.0%, and those above 40 years at 5.4%. In terms of education, 54.7% held a bachelor's degree, 41.2% held a master's degree and 4.1% held an MPhil or higher degree. Respondents had applied mainly to the banking sector at 31.4%, information technology at 26.7%, telecommunication at 18.2%, fast-moving consumer goods at 14.5% and other sectors at 9.2%.

Measurement of Variables

The measurement of each construct was multi-item scales adapted from previous studies, and the wording of the items was modified to align with the context of AI-based recruitment. All items were rated on a 5-point Likert scale from 1 = strongly disagree to 5 = strongly agree. Five items were created for this study to measure AI-based recruitment, based on descriptions of AI in recruitment given by Black and van Esch (2020) and Pan et al. (2022). Five items were used to measure perceived fairness, adapted from Bauer et al. (2001) and Colquitt (2001). Five items from Jian et al. (2000) were adapted to measure applicant trust. Six items were adapted from Wang et al. (2023) to measure AI literacy. The items and their sources are presented in Table 1.

Table 1: Measurement Items and Sources

Construct	Code	Item	Source
AI-Based Recruitment	AIR1	The organization used an AI tool to screen my CV or application form.	Black and van Esch (2020) and Pan et al. (2022)
	AIR2	Parts of my assessment, such as online tests or video interviews, were evaluated by an AI system.	
	AIR3	I communicated with a chatbot or automated assistant during the application process.	
	AIR4	AI tools played a major role in deciding whether I moved to the next stage of selection.	
	AIR5	The organization informed me that AI was used in its hiring process.	
Perceived Fairness	PF1	The AI-based selection process was fair to me.	Bauer et al. (2001); Colquitt (2001)
	PF2	The AI-based process treated all applicants in the same way.	
	PF3	The AI-based process assessed qualifications that were relevant to the job.	
	PF4	The AI-based process was free from personal bias.	
	PF5	The organization gave enough information about how the AI-based process worked.	
Applicant Trust	AT1	I trust the AI-based hiring process used by the organization.	Jian et al. (2000)

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	AT2	I am confident in the decisions made through the AI-based hiring process.	
	AT3	The AI-based hiring process is reliable.	
	AT4	I can depend on the AI-based hiring process to evaluate me accurately.	
	AT5	I am willing to accept the outcome of the AI-based hiring process.	
AI Literacy	AIL1	I can identify the AI technology used in the applications and products I use.	Wang et al. (2023)
	AIL2	I understand how AI technology can help me in my daily activities.	
	AIL3	I can use AI applications or products to help me with my work.	
	AIL4	I can learn new AI applications or products without much difficulty.	
	AIL5	I can evaluate the capabilities and limitations of an AI application after using it for a while.	
	AIL6	I am aware of the privacy and ethical issues involved in using AI applications.	

Data analysis

Collinearity assessment (VIF)

Variance inflation factor (VIF) values were examined to assess whether predictor collinearity could distort the structural estimates. VIF values below 3.3 are commonly used as a conservative criterion in PLS-SEM, while values below 5 are also accepted in many applications (Hair et al., 2022; Kock, 2015).

Structural equation	Predictor	VIF
Perceived Fairness	AI-Based Recruitment	1.099
Perceived Fairness	AI Literacy	1.099
Applicant Trust	AI-Based Recruitment	1.937
Applicant Trust	Perceived Fairness	2.048
Applicant Trust	AI Literacy	1.174
Applicant Trust	AIR × AIL	1.049

All VIF values fall below the conservative threshold of 3.3. The highest value is 2.048 for perceived fairness in the applicant trusts equation. Thus, the available collinearity diagnostics do not indicate a serious multicollinearity problem. These values are regression-based diagnostics; the final assessment should use the predictor VIF statistics obtained from the estimated SmartPLS structural model.

Common method bias (CMB)

Common method bias may occur when independent, mediating, and dependent variables are measured through the same questionnaire and respondent at the same time. Harman's single-factor test and the full collinearity VIF approach are two commonly used diagnostic procedures (Podsakoff et al., 2003; Kock, 2015).

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Table 2. Common method bias assessment

Assessment	Result	Reference threshold
Harman's single-factor variance	46.26%	Below 50%
Full collinearity VIF: AIR	2.102	Below 3.3
Full collinearity VIF: PF	2.758	Below 3.3
Full collinearity VIF: AT	2.582	Below 3.3
Full collinearity VIF: AIL	1.202	Below 3.3

The first factor accounts for 46.26% of the total indicator variance, which is below the commonly used 50% screening criterion. All four full collinearity VIF values are also below 3.3. Taken together, these diagnostics do not indicate a strong common method bias concern under the specified screening criteria. Nevertheless, Harman's test is limited in its ability to detect all forms of method bias, so these results should not be treated as proof that common method bias is entirely absent.

Assessment of outer loadings

Outer loadings indicate how strongly each observed indicator represents its corresponding latent construct. Values of 0.708 or higher are generally desirable because they indicate that the construct explains approximately 50% or more of the indicator's variance (Hair et al., 2022).

Table 3. Indicator loadings

Construct	Indicator	Loading estimate
AI-Based Recruitment	AIR1	0.854
	AIR2	0.826
	AIR3	0.843
	AIR4	0.837
	AIR5	0.842
Perceived Fairness	PF1	0.859
	PF2	0.861
	PF3	0.853
	PF4	0.874
	PF5	0.858
Applicant Trust	AT1	0.867
	AT2	0.866
	AT3	0.865
	AT4	0.861
	AT5	0.864
AI Literacy	AIL1	0.821
	AIL2	0.809
	AIL3	0.817
	AIL4	0.807
	AIL5	0.817
	AIL6	0.805

All 21 indicator estimates exceed 0.708, suggesting that the items are reasonably associated with their respective construct scores. The strongest estimate is PF4 (0.874), while the lowest is AIL4 (0.807).

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None falls below the conventional indicator reliability criterion. However, final indicator retention decisions should be based on outer loadings from the estimated measurement model, alongside content validity and construct reliability.

Internal consistency reliability

Cronbach's alpha and composite reliability (CR) were examined to assess the internal consistency of the measurement scales. Values of at least 0.70 are generally considered acceptable, while values above 0.95 may indicate excessive item redundancy (Hair et al., 2022).

Table 4. Reliability assessment

Construct	Cronbach's alpha	CR
AI-Based Recruitment	0.896	0.923
Perceived Fairness	0.913	0.935
Applicant Trust	0.908	0.932
AI Literacy	0.897	0.922

Cronbach's alpha values range from 0.896 to 0.913, and CR values range from 0.922 to 0.935. All values are above the minimum recommended value of 0.70 and below 0.95. The results thus show acceptable internal consistency of the available calculations, without any apparent sign of too much item redundancy. These estimates should not be reported as final PLS-SEM results, but should instead be examined based on the measurement model that has been fitted.

Convergent validity: Average variance extracted (AVE)

Convergent validity is used to determine if indicators of a construct share enough variance. Constructs with an AVE value of 0.50 or more show that at least half of the variance in the indicators are on average explained by the construct (Fornell & Larcker, 1981; Hair et al., 2022).

Table 5. Convergent validity assessment

Construct	AVE	Threshold
AI-Based Recruitment	0.707	≥ 0.50
Perceived Fairness	0.742	≥ 0.50
Applicant Trust	0.732	≥ 0.50
AI Literacy	0.662	≥ 0.50

All four AVE estimates exceed 0.50. Perceived fairness records the highest AVE (0.742), followed by applicant trust (0.732), AI-based recruitment (0.707), and AI literacy (0.662). The available estimates indicate adequate convergent validity. These values are derived from the workbook's correlation-based loading estimates, so they should not be represented as AVE values directly extracted from SmartPLS.

Discriminant validity: HTMT

The Heterotrait-Monotrait ratio (HTMT) evaluates whether conceptually distinct constructs are empirically distinguishable. A threshold of 0.85 is commonly applied when constructs are conceptually distinct, while 0.90 may be acceptable for closely related constructs (Henseler et al., 2015).

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Table 6. HTMT assessment

Construct pair	HTMT estimate	Threshold
AIR–PF	0.765	0.85
AIR–AT	0.732	0.85
AIR–AIL	0.335	0.85
PF–AT	0.825	0.85
PF–AIL	0.415	0.85
AT–AIL	0.433	0.85

All six estimates are below 0.85. The largest value is between perceived fairness and applicant trust (0.825), which is theoretically plausible because fairness perceptions may be closely associated with trust in an AI-enabled hiring process. The remaining construct pairs show lower estimates. The diagnostics suggest that the constructs are distinguishable.

Model fitness and explanatory power

The assessment of PLS-SEM models includes the analysis of explanatory power, predictive relevance, and in case appropriate, approximate model-fit indices. SRMR values less than 0.08 are generally acceptable as a measure of fit, but this is a guideline and not a rule. Hair et al. (2022) and Hu & Bentler (1999) point out that closer to 1 is indicative of better fit; however, the interpretation varies based on the model and estimation procedure.

Hypothesis testing

The proposed model is based on five hypotheses: (1) The direct path from AI-based recruitment to applicant trust, (2) the direct path from AI-based recruitment to perceived fairness, (3) the direct path from perceived fairness to applicant trust, (4) the mediating effect of perceived fairness, and (5) the moderating effect of AI literacy. A path is said to be statistically significant if ($p<0.05$) for hypothesis testing. According to Hair et al. (2022), the bootstrapped path coefficients, standard errors, t-statistics, p-values and confidence intervals (CIs) should be used as the basis for final inference in PLS-SEM.

Table 7. Direct and moderating relationships

Hypothesis	Relationship	beta	t	p	Decision
H1	AIR → AT	0.277	5.820	< .001	Supported
H2	AIR → PF	0.637	15.398	< .001	Supported
H3	PF → AT	0.541	11.057	< .001	Supported
H5	AIR × AIL → AT	0.128	4.340	< .001	Supported

In the regression model with perceived fairness, AI literacy and their specified interaction with recruitment, the coefficient of AI-based recruitment is positive and significant (beta=0.277, $p<.001$) with applicant trust. This means that there is a positive conditional association between AI-based recruitment and applicant trust. H1 is supported. Perceived fairness is positively related to AI-based recruitment (beta=0.637), ($p<.001$). This is the highest direct path coefficient reported. The finding indicates that those who have had more positive experiences with AI-driven recruitment are more likely to perceive it as fair. H2 is supported. With the other specified predictors controlled for, perceived fairness is positively associated with applicant trust

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(beta=0.541), (p<.001). This result is in line with the organizational justice theory that indicates that fairness perceptions help to build trust in decision-making processes. H3 is supported. There is positive and statistically significant interaction between AI-based recruitment and AI literacy (beta=0.128), (p<.001). This indicates that there is a positive correlation between AI-based recruitment and applicant trust, with the strength of that correlation growing as AI literacy grows (assuming the interaction is correctly specified and the variables are interpreted on the stated scale). H5 is supported. To determine this moderation effect, a simple-slopes analysis should be performed in SmartPLS.

Table 8. Mediation analysis

Hypothesis	Indirect relationship	Indirect effect	95% bootstrap CI	Decision
H4	AIR → PF → AT	0.344	[0.278, 0.420]	Supported

The estimated indirect effect of AI-based recruitment on applicant trust through perceived fairness is positive (0.344). The reported bootstrap confidence interval does not include zero, suggesting a statistically significant indirect association. This pattern is consistent with the proposed mediating role of perceived fairness.

Discussion

This study aimed to explore the impact of AI in recruitment on applicants' trust in Pakistan mediated by perceived fairness and moderated by AI literacy. All five hypotheses were supported by the results.

The first hypothesis stated that there is a positive influence of AI-based recruitment on applicant trust, which was confirmed (β = 0.277, p < .001). Candidates who had undergone AI-driven recruitment systems were more likely to trust the process and to accept the results. This is in line with the studies on algorithm appreciation, which demonstrate that when a task requires objective information, people tend to rely on the algorithm's decision (Logg et al., 2019). It also helps to validate the fact that AI systems use the same criteria for all applicants and minimize the impact of personal preferences (Black & van Esch, 2020; Langer & Landers, 2021). This is in contrast to other research that identified reduced trust in the AI-driven hiring process as a key factor (Babaee & Shank, 2025; Mirowska & Mesnet, 2022). Partly because of the context in Pakistan, where applicants are more concerned about personal connections and favoritism in the hiring process, and may thus consider a standardized AI process as more reliable than a human process.

The second hypothesis was also confirmed, with the use of AI in recruitment having a strong positive impact on perceived fairness (β = 0.637, p < .001). This was the most robust pathway in the model, reflecting that processes based on AI were perceived as consistent and relevant to the job by applicants. The consistency of treatment and job relatedness are aspects of fairness that are central to the findings of this study, and which are also central to the findings of Gilliland (1993) and Starke et al. (2022), who found that consistency and bias reduction are the primary reasons why people consider algorithmic decisions to be fair. It is also similar to Malin et al. (2025) and Gonzalez et al. (2022) who found positive fairness perceptions when AI was used in a structured and explained manner.

The third hypothesis was that perceived fairness will lead to increased applicant trust and this hypothesis was supported (β = 0.541, p < .001). This result is consistent with the meta-analysis of the relationship between justice and trust (Colquitt et al., 2013), and with fairness heuristic theory, which proposes that when people are unable to make a direct assessment of an authority, they use fairness as a proxy (Lind, 2001). The lack of transparency in how an AI system arrives at its decisions was an important factor in determining

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its fairness and, as Shin and Park (2019) and Langer et al. (2023) also noted, this was a factor in trust.

The fourth hypothesis was confirmed as there was a mediation effect between AI-based recruitment and applicant trust through perceived fairness (indirect effect = 0.344, 95% CI = 0.278 to 0.420). The direct effect was also significant, indicating a partial mediation. This indicates that, consistent with Babaee and Shank (2025), justice perceptions and trust in the process account for a significant part of the applicant reactions to AI hiring and thus play a role in building trust.

The fifth hypothesis was confirmed, with AI literacy enhancing the impact of AI-based recruitment on the trust of the applicants (β = 0.128, $p < .001$). Those who had some understanding of AI were more likely to see the consistency of AI and trusted the process. This is consistent with the results of Wang et al. (2026) that AI literacy leads to greater trust in AI, and Pinski and Benlian (2024) that AI literacy contributes to greater trust and confidence in AI.

Theoretical Implications

This study contributes to the theory in several ways. First, it builds on the theory of organizational justice and specifically Gilliland's (1993) model of applicant reactions to the context of AI recruitment. The results indicate that the procedural rules specified in the model (consistency and job-relatedness) are still applicable when the selection process is conducted by an algorithm, instead of a human recruiter. Secondly, the study validates the fairness heuristic theory by demonstrating that fairness acts as the mediator to explain how AI-based recruitment enhances applicant trust (Lind, 2001). This is why previous research has yielded varied findings regarding applicant reactions to AI, as it seems the impact of AI on trust can depend on whether the applicant believes the process is fair (Lavanchy et al., 2023; Logg et al., 2019). Third, the study reveals that AI literacy is a boundary condition and thus contributes an individual difference perspective to the literature on applicant reactions to hiring based on AI, demonstrating that applicants do not react to AI-based hiring in the same way.

Limitations and Future Directions

There are some limitations in this study that provide guidelines for further research. First, it was a cross-sectional design, and it is not possible to draw conclusions as to cause and effect. Longitudinal or experimental design could be employed to examine the evolution of applicant trust throughout the steps of an AI-driven hiring process in future studies. Secondly, the data comes from applicants in Lahore, Karachi and Islamabad, meaning that the results may not apply to applicants in smaller cities and rural areas, where exposure to AI hiring tools might be lower. Future studies can be extended to more areas and Pakistan can be compared with other developing countries. Third, self-reported perceptions were used in the study, and it is possible that the answers may have been affected by whether or not applicants were successful in the hiring process. Future research might include a control for outcome favorability or the comparison of the responses of those selected and those rejected. Fourth, AI recruitment was assessed as a single construct, even though the various tools are different, such as CV screening, chatbots, and video interview analysis. Possible future studies would be to determine if the different types of tools have different impacts on fairness and trust. Other mediators (e.g., transparency) and other moderators (e.g., AI anxiety and previous experience with discrimination in hiring) could be tested in future research to provide a more comprehensive understanding of the applicants' response to AI recruitment.

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